Processing String Fusion Approach Investigation for Automated Sea Mine Classification in Shallow Water

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***Abstract*- A novel sea mine computer-aided-detection / computer-aided-classification (CAD/CAC) processing string has been developed. The overall CAD/CAC processing string consists of pre-processing, adaptive clutter filtering (ACF), normalization, detection, feature extraction, feature orthogonalization, optimal subset feature selection, classification and fusion processing blocks. The range-dimension ACF is matched both to average mine highlight and shadow information, while also adaptively suppressing background clutter. For each detected object, features are extracted and processed through an orthogonalization transformation, enabling an efficient application of the optimal log-likelihood-ratio-test (LLRT) classification rule, in the orthogonal feature space domain. The classified objects of 4 distinct processing strings are fused using the classification confidence values as features and "M-out-of-N", or LLRT-based fusion rules. The utility of the overall processing strings and their fusion was demonstrated with new shallow water high-resolution sonar imagery data. The processing string detection and classification parameters were tuned and the string classification performance was optimized, by appropriately selecting a subset of the original feature set. Two significant improvements were made to the CAD/CAC processing string by employing sub-image adaptive clutter filtering (SACF) and utilizing a repeated application of the subset feature selection / LLRT classification blocks. It was shown that LLRT-based fusion of the CAD/CAC processing strings outperforms the "M-out-of-N" algorithms and results in up to an eight-fold false alarm rate reduction, compared to the best single CAD/CAC processing string results, while maintaining a constant correct mine classification probability**.

I. INTRODUCTION

The long-term goal of this project is to develop robust, automated sea mine detection, classification and fusion algorithms to be utilized by imaging sonars on-board of unmanned underwater vehicles (UUV) operating in shallow water (SW) or very shallow water (VSW) environments. This technology will help enable the mine-countermeasures (MCM) vehicle operation in the VSW, thus substituting Navy divers and marine mammals that are currently performing this extremely hazardous task.

The near-term objective of this project is to demonstrate automated sea mine detection and classification in the VSW, using CAD/CAC and fusion algorithms that are being developed by 4 research teams at the Naval Surface Warfare Center (NSWC) Coastal Systems Station (CSS), Raytheon, Alphatech, and Lockheed Martin (LM). This work is in support of mine-hunting demonstrations for ONR's Ocean Engineering and Marine Systems programs.

This paper builds on LM's previous work [1]-[9] in the automated detection and classification of sea mines in sonar imagery. It discusses two significant CAD/CAC processing string improvements: the first entails utilizing a sub-image adaptive clutter filter instead of the single adaptive filter per image that was previously employed, whereas the second entails the repeated application of the subset feature selection, feature orthogonalization and LLRT classification processing blocks in a cascade fashion [10], [11]. This latter approach was first utilized by Dobeck [12] and was referred to as a "classifier anding" procedure.

The overall system performance can of course be significantly enhanced by fusing the outputs of distinct processing strings. In recent papers the authors presented the results of fusing the outputs of 3 processing strings and utilizing a VSW dataset [6]-[9], or a SW dataset [10]. The authors most recent paper presented the results of fusing 4 distinct processing strings and utilizing a new SW dataset [11]. This paper presents the results of fusing the improved LM CAD/CAC processing string with the 3 other ones and utilizing the same latest SW dataset. The fusion algorithms evaluated here include "M-out-of-N" and feature orthogonalization / LLRT-based algorithms.

II. CAD/CAC STRING DESCRIPTION AND PROCESSING RESULTS

A. Baseline CAD/CAC Processing String

An automatic, robust, adaptive clutter suppression, sea mine detection and classification processing string has been developed and applied to high-resolution sonar imagery data. Fig. 1 shows this baseline CAD/CAC processing string, which includes pre-processing, *adaptive clutter filtering (ACF*), normalization and detection, feature extraction and orthogonalization, best subset feature selection and LLRT classification processing blocks.

The pre-processing block contains pre-normalization, clipping and data decimation blocks. Normalization reduces data non-homogeneity. A combination feed-forward and backward normalizer was employed, which computes water column information and was developed by Dobeck [13]. After normalization, data clipping better conditions the data for ACF processing, by resulting in a more stable target signature for the algorithm design and application. Subsequently applied data decimation reduces the overall processing string implementation complexity and again facilitates ACF design and application.

The ACF is an adaptive linear FIR filter, which is optimal in the Least Squares (LS) sense and is applied to low-resolution data. It performs simultaneous background clutter suppression and peak target preservation by exploiting differences between clutter and target correlation

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **01 SEP 2003**	2. REPORT TYPE **N/A**	3. DATES COVERED **-**
4. TITLE AND SUBTITLE **Processing String Fusion Approach Investigation for Automated Sea Mine Classification in Shallow Water**		5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Lockheed Martin, Naval Electronics and Surveillance Systems, Syracuse, NY 13221-4840**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR'S ACRONYM(S) 11. SPONSOR/MONITOR'S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT **Approved for public release, distribution unlimited**		
13. SUPPLEMENTARY NOTES **See also ADM002146. Oceans 2003 MTS/IEEE Conference, held in San Diego, California on September 22-26, 2003. U.S. Government or Federal Purpose Rights License**		
14. ABSTRACT		
15. SUBJECT TERMS		

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**UU**	**8**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

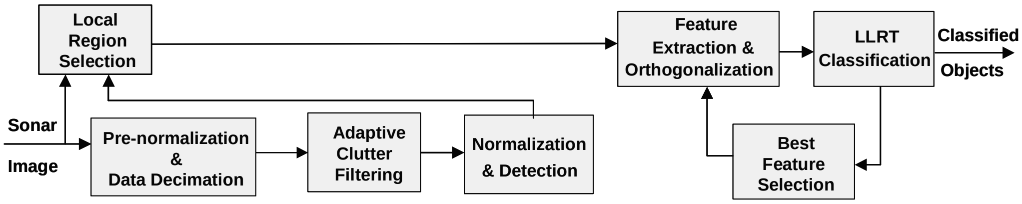

Fig. 1. Baseline mine detection and classification processing string.

characteristics. In the latest algorithm version, a 1-dimensional range-only ACF, that was matched to both average highlight and shadow target shape information, was applied after mean removal. A *wide-sense stationary covariance* [5] model is utilized in the algorithm design, which significantly reduces the algorithm implementation complexity, thus enabling an easy implementation of the overall processing string in real-time.

The ACF block output is processed through a crossrange domain, whole column, global normalizer, which employs negative and small value data clipping and removes any remaining non-stationarities in the data. Subsequently, detection processing is applied, consisting of thresholding, clustering of exceedances (based on the maximum expected mine target size), application of secondary thresholding (discarding all detections that are point-like) and limiting the number of detections.

Referring to Fig. 1, features or clues are extracted for each detected contact, using high-resolution input sonar data, centered at the corresponding local region. Subsequently, the features are processed through an *orthogonalization transform*, which enables an efficient application of the optimal *LLRT classification* rule in the orthogonal feature space domain. Another important point is the utilization of software tools for the selection of feature and LLRT classifier parameters and the *selection of a subset of the features ("the best features")* using a training set, and thus optimizing the processing string classification performance.

B. Improved CAD/CAC Processing String

1) Sub-image Adaptive Clutter Filter (SACF)

The baseline CAD/CAC processing string utilized a single ACF per image. This algorithm computed the background covariance statistics over the whole image and was matched to a signature vector obtained by averaging over all the training set mine signatures. The baseline ACF algorithm performed well, since typically the images inputted into the ACF are rather homogeneous, since they have already been pre-normalized. On the other hand, a modified algorithm that breaks the image into sub-images and computes a different ACF for each sub-image offers advantages, since it can better adapt to the covariance statistics of each sub-image and to the signature variations in each sub-image (e.g. mines at longer ranges are known to have longer shadows).

The optimum filter formulation of the SACF algorithm involves the minimization of the cost function, for the ith sub-image of

$$J_i = 0.5\, \mathbf{w}_i^{\mathbf{T}} \mathbf{R}_i \mathbf{w}_i - \lambda\, (\mathbf{w}_i^{\mathbf{T}} \mathbf{s}_i - 1) - \mu\, (\mathbf{w}_i^{\mathbf{T}} \mathbf{1} - 0)\,, \qquad (1)$$

where $\mathbf{w}_i$ is the adaptive filter weight vector, $\mathbf{w}_i^{\mathbf{T}}$ denotes vector transpose, $\mathbf{R}_i$ is the clutter covariance matrix, $\mathbf{s}_i$ is the average target signal signature within the filter window, $\mathbf{1}$ is a constant vector whose components are all equal to 1 and λ and μ are Language multipliers. The first term in (1) refers to clutter minimization, the second term is a target preservation constraint and the third term is a mean removal constraint, such that there are no mean mismatches after application of the SACF algorithm to different sub-images (*this is necessary since post ACF processing involves further image normalization*).

Minimization of (1) results in the normal equations

$$\mathbf{R_i}\, \mathbf{w}_i = \lambda\, \mathbf{s}_i + \mu\, \mathbf{1}\,, \qquad (2)$$

which are solved for the optimum adaptive linear filter $\mathbf{w}_i$.

In the SACF procedure, for each sub-image at each spatial location the 1-dimensional range-only search-box contents are scanned into a local vector $\mathbf{x_i}(k)$ and the corresponding snapshot of the local covariance $\mathbf{R_i}(k)$ is computed. Sliding the search-box over the whole sub-image and adding all the local covariances, the overall accumulated sub-image covariance $\mathbf{R_i}$ is then computed as

$$\mathbf{R}_i = \frac{1}{P}\sum_{k=1}^{P}\mathbf{R}_i(k) = \frac{1}{P}\sum_{k=1}^{P}\mathbf{x}_i(k)\,\mathbf{x}_i^{T}(k)\ . \qquad (3)$$

Substituting (3) and the average target signature vector $\mathbf{s_i}$ into (2) and solving, using a Cholesky decomposition of the covariance matrix followed by back substitutions, yields the optimal adaptive spatial filter $\mathbf{w_i}$

$$\mathbf{w_i} = \mathbf{R_i}^{-1} \mathbf{A_i} \,/\, (\mathbf{A_i}^{\mathbf{T}} \mathbf{R_i}^{-1} \mathbf{A_i})\, \mathbf{b}\,, \qquad (4)$$

where matrix $\mathbf{A_i}$ and vector $\mathbf{b}$ are defined as

$$\mathbf{A_i} = [\ \mathbf{s_i}\ \ \mathbf{1}\ ]\,,$$
$$\mathbf{b}^{\mathbf{T}} = [\ 1\ \ 0\ ]\,.$$

Finally, the data is filtered as

$$y_i(k) = \mathbf{w_i}^{\mathbf{T}}\, \mathbf{x_i}(k)\,. \qquad (5)$$

The SACF procedure was outlined by (1)-(5). Typically, an average target signature vector $\mathbf{s_i}$ is estimated from all the training set mine signature data in the ith sub-image. For each

target in the training set the 1-dimensional filter window is centered at the target mask, with the largest value normalized to 1. The contents of the search-box are then scanned into a vector to compute the normalized signature vector $\mathbf{s_{ik}}$ for the k^{th} target. Subsequently, an average signature is computed by averaging the signatures of all the members belonging to the training class as

$$\mathbf{s}_i = \frac{1}{M}\sum_{k=1}^{M}\mathbf{s}_{ik} \quad . \tag{6}$$

2) *Cascade Classification*

Each dataset is typically split into training and test sets, each set containing roughly half the images and half the targets. The classifier is trained on the training set only, to help avoid over-training the classifier, but performance is optimized over the whole dataset. Cascade classification entails repeated application of the classification stage. After the first stage, classifier parameters are selected in such fashion that all targets are correctly called, with each classification stage discarding as many false alarms as possible.

With LM's cascade classifier design, the subset feature selection, feature orthogonalization and LLRT classification process is repeated until classification performance has stabilized. In each stage, the best subset of features, the appropriate number of LLRT histogram bins and the classification threshold are selected to optimize the corresponding classification performance. Each progressing stage results in a diminishing false alarm feature set, whereas the target training and test feature sets remain fixed.

The cascade classification technique is illustrated in Fig. 2. During the training phase of the algorithm, it is determined how many times to apply the classification process (typically 3-4 times), and each stage determines and stores the classification threshold, the best subset of features, the corresponding orthogonalization transformation matrix, the number and boundaries of the histogram bins and the corresponding LLRT values in the orthogonal feature space domain.

In the testing phase of the algorithms all these parameters are fixed and are looked up from a library. The performance stabilizer block becomes then a counter and a memory storage pointer of the classification stage parameters. After processing feature data 3-4 times, the final classified objects are fed to the output stage. The improved CAD/CAC processing string entails replacing the classification stage of Fig. 1 (the 3 right hand blocks) with Fig. 2.

C. *Processing String Performance Evaluation Results*

Lockheed Martin evaluated the ACF, detection and classification algorithm performance with a new shallow water sonar data set, collected off the coast of Southern California and in the Gulf of Mexico in 2001. The dataset consisted of 113 images, containing a total of 86 targets [11]. The data was split into a training set (containing half the images and half the targets) and a test set, both of which were utilized for the algorithm performance evaluation and testing phase.

The sonar image data was first processed through the baseline Lockheed Martin (LM) CAD/CAC processing string of Fig. 1. The pre-processing block included: pre-normalization and clipping the sonar images; averaging and employing a 2:1 data decimation factor in both range and crossrange dimensions, and applying mean removal. Data was subsequently processed through a range-only 31-tap ACF that was matched both to average highlight and shadow shape information, and a global post-ACF normalizer, with negative data and noise level clipping. Subsequently data was processed through the detection block, and the detection parameters were optimized.

After detection processing, high-resolution clues were extracted from the input sonar data. Originally, each detected object was characterized by an 11-dimensional feature vector, described in Fig. 3. The thresholds and window sizes of the feature parameters were selected to optimize the LLRT classifier performance. The classifier was trained on the training set. Performance evaluation results were with the whole dataset.

The overall processing string mine classification performance was optimized by selecting a subset of the features, "the best features". The baseline LM CAD/CAC string performance with the SW dataset, when using the "7 best features", was 0.73 average false alarms/image (FAPI), while correctly classifying 78 out of 86 targets, P_dP_c=0.907 [11].

The baseline LM CAD/CAC processing string used a single ACF per image algorithm. The first significant improvement of the processing string, described in Section II.B.1, entailed splitting the image into sub-images and designing sub-image adaptive clutter filters. A preliminary investigation of this SACF algorithm showed that splitting the image into 3 sub-images, and designing and applying 3 SACFs, resulted in a significant performance improvement. The improved SACF-based CAD/CAC string performance was FAPI=0.67, while correctly classifying 80 out of 86 targets, P_dP_c=0.93. The baseline ACF and improved SACF CAD/CAC string results are summarized in Table 1.

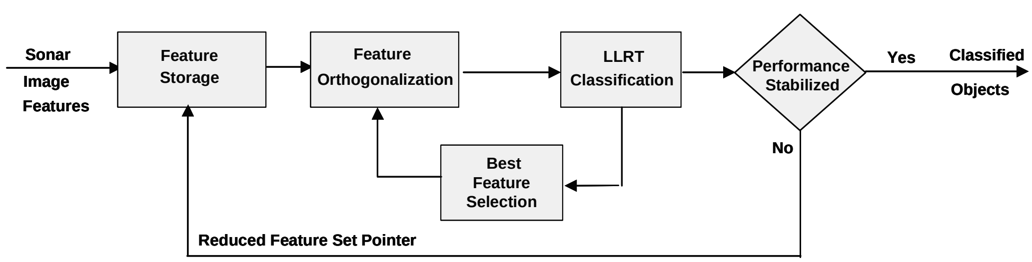

Fig. 2. Cascade classification technique.

Feature Listing	Selected Feature at Classifier Stage #		
	1	2	3
1. Peak Magnitude	★		★
2. # Highlight Pixels in 5x5 Window		★	★
3. # Highlight Pixels in a L_1XL_2 Wind.	★	★	★
4. Normalized Variance	★	★	★
5. Skew	★	★	
6. Kurtosis	★		★
7. Length			★
8. Width	★	★	
9. Orientation		★	
10. Shadow Pixel Count	★	★	
11. Shadow Length	★	★	
# of Selected Features	8	8	6

Fig. 3. Feature listing and selected features (denoted by ★) at each classification stage.

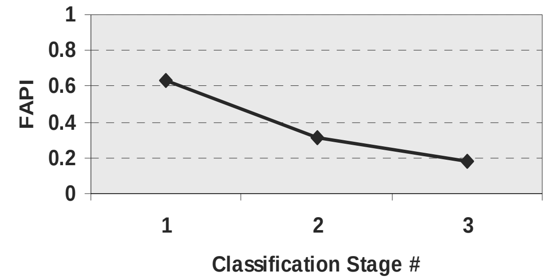

Fig. 4. Cascade classifier results - P_dP_c=0.93.

The 2nd improvement of the CAD/CAC processing string of Section II.B.2, uses the multistage classifier of Fig. 2. Its mine classification performance with the SW dataset is summarized in Fig. 4. Each classification stage reduces false alarms, while maintaining a constant mine classification probability of P_dP_c=0.93. Processing data through a multi-stage classifier 3-times results in a FAPI=0.177, which corresponds to a 3.6:1 false alarm reduction vs. the single-stage classifier performance. Referring to Fig. 4, it is noted that false alarm reduction performance has nearly-stabilized after the 3rd stage, i.e. a small additional false alarm reduction is provided by the 3rd stage, which explains why it was chosen to process data 3 times through our multi-stage classifier. Also, notice that the early classification stages provide a more significant false alarm reduction than the later ones. Additionally, for each classification stage, we select an optimal feature subset as shown in Fig. 3.

It should be noted that, with each new dataset there are always CAD/CAC processing string parameters that need to be determined, to optimize detection and classification string performance. These include: noise clipping factor, SACF reference signatures, detection and classification thresholds, feature window parameters and multi-stage classifier parameters, including classification thresholds, number of histogram bins, subsets of best features, LLRT histogram values and orthogonalization transformation matrices, all determined during the training phase of the algorithms.

III. CAD/CAC STRING FUSION RESULTS

A. Fusion Approach

The authors approach in this paper is to fuse the results of 4 drastically different CAD/CAC processing strings [11]. The 1st CAD/CAC processing string was developed by Lockheed Martin-Syracuse (Tom Aridgides and Manuel Fernandez [1]-[11]), the 2nd was developed by CSS (Gerald J. Dobeck [12]-[16]), the 3rd was developed by Raytheon (Charles Ciany, Jim Huang, et. al. [17]), whereas the 4th was developed by Alphatech (Marty Bello [18]), all under ONR sponsorship.

TABLE 1. BASELINE ACF AND IMPROVED SACF CAD/CAC STRING PERFORMANCE SUMMARY

CAD/CAC String	*PdPc*	*FAPI*
Improved SACF-based	0.930	0.63
Baseline ACF-based	0.907	0.73

The fusion of algorithms is a very powerful tool, since each algorithm is looking at the same data from a different perspective. This is due to the fact that each algorithm is based on different mathematical, statistical, and geometric theories, and thereby emphasizes (or de-emphasizes) different characteristics of the data (clutter and targets). Therefore much can be gained through the algorithm fusion, especially in false alarm reduction, where typically few false alarms are common to all algorithms.

The outputs of the Lockheed Martin, CSS, Raytheon and Alphatech CAD/CAC strings were fused as shown in Fig. 5. Calls by different algorithms were grouped into the same call, based on distance criteria derived from the expected sizes of targets and also accounting for differences of the various algorithms in computing the centroid of the target. The authors of this paper utilized a variety of fusion algorithms, including: "M-out-of-N", and orthogonal LLRT-based. The confidences of the 4 CAD/CAC string outputs were used as features for the orthogonal LLRT-based algorithm.

B. Fusion Results

The 113 SW sonar images were processed through the tuned and improved Lockheed Martin, CSS, Raytheon and Alphatech CAD/CAC processing strings. The single string CAD/CAC processing results are summarized in Table 2. In Table 2, Ndet denotes the number of mine targets correctly called by an algorithm, P_dP_c denotes the corresponding probability of correct mine classification, nfa denotes the number of false alarms and FAPI denotes the average number of false alarms per image.

Each string output j (j=1,2,3,4) generated a number of calls, indicating the corresponding image file, the call location X_{ij}, Y_{ij} and a confidence factor C_{ij}, associated with each call i.

For each image file, a call i by algorithm j and a call m by algorithm n are attributed to the same object, iff:

$$\mathrm{dis}\{ (X_{ij}, Y_{ij}), (X_{mn}, Y_{mn}) \} < \mathrm{dis}_{min}, \quad (7)$$

where dis_{min} is based on the largest mine size. If algorithm j has detected an object i, then the corresponding confidence

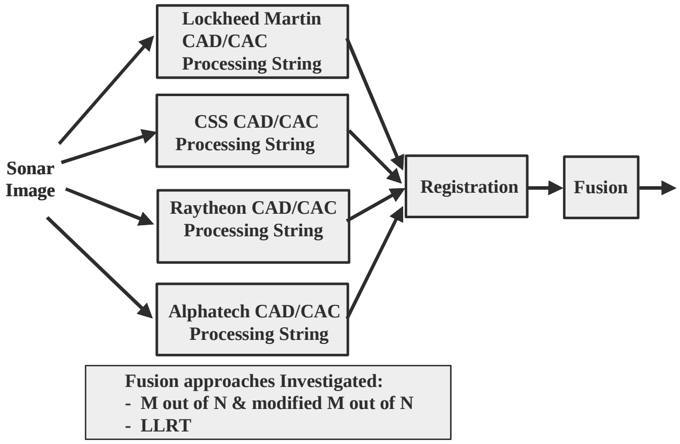

Fig. 5. CAD/CAC string fusion.

value C_{ij} is such that,

$$0.5 \leq C_{ij} \leq 1 , \tag{8}$$

(where C_{ij} = 0.5 denotes 50% confidence about the classification decision and C_{ij} = 1 denotes 100% confidence).

After registration of calls by different algorithms, each call is characterized by a 4-dimensional feature vector

$$C_i = [\ C_{i1}\ \ C_{i2}\ \ C_{i3}\ \ C_{i4}\ ] , \tag{9}$$

where C_{ij}=0 denotes that algorithm j did not classify this object.

Lockheed Martin has developed and refined "M-out-of-N" and orthogonal LLRT-based algorithms to fuse the data and has analyzed the fusion algorithm performance. The baseline "M-out-of-N" algorithms do not use actual confidence values, but LLRT-based ones do.

1) M out of N Fusion Results

The authors employed the commonly utilized "M-out-of-N" fusion rules to combine the individual CAD/CAC string outputs. Calls were grouped together prior to the application of the various fusion rules. The following rules were utilized:

- "Alg. N +1" (a fusion call is declared iff it was made by algorithm N, where N=1, …,4, and at least 1 more other algorithm).
- "1-out-of-4" (a fusion call is declared iff it was made by at least 1 out of 4 algorithms – this is the same as an ORing rule).
- "2-out-of-4" (a fusion call is declared iff it was made by at least 2 out of 4 algorithms).
- "Modified 2-out-of-4" (a fusion call is declared iff it was made by at least 2 out of 4 algorithms and the sum of the confidence values was greater than 1.298, i.e. $1.298 \leq \Sigma\, C_{ij}$, this threshold value was determined from the data, by looking at all fused target calls and determining the minimum aggregate confidence value).
- "3-out-of-4" (a fusion call is declared iff it was made by at least 3 out of 4 algorithms).

TABLE 2. SINGLE CAD/CAC STRING PERFORMANCE SUMMARY

CAD/CAC String	*Ndet*	*PdPc*	*nfa*	*FAPI*
Alg. 1	80	0.930	20	0.177
Alg. 2	78	0.907	41	0.363
Alg. 3	77	0.895	69	0.611
Alg. 4	74	0.860	69	0.611

- "Modified 3-out-of-4" (a fusion call is declared iff it was made by at least 3 out of 4 algorithms and the sum of the confidence values was greater than 1.803, i.e. $1.803 \leq \Sigma\, C_{ij}$, this threshold value was also determined from the data, by looking at all fused target calls and determining the minimum aggregate confidence value).
- "4-out-of-4" (a fusion call is declared iff it was made by all 4 algorithms – this is the same as an ANDing rule).

The "M-out-of-N" fusion results are summarized in Table 3. Comparing these results to the individual CAD/CAC string results of Table 2, the following fusion performance processing improvements are noted:

- "Alg. N+1" fusion provides between 2.3:1 and 3.1:1 false alarm reduction over the CAD/CAC string N alone, when maintaining the same P_dP_c.
- "1 out of 4" algorithm fusion provides the capability to correctly call all targets, but at a cost of a high false alarm rate, FAPI=1.4.
- "2-out-of-4" fusion provides a high mine classification capability, P_dP_c=0.942, with only FAPI=0.283.
- "Modified 2-out-of-4" fusion provides an additional 1.3:1 false alarm reduction, over "2-out-of-4" fusion.
- "3-out-of-4" and "modified 3-out-of-4" fusion both result in a very low false alarm rate, FAPI=0.062, at P_dP_c=0.895.
- "4 out of 4" algorithm fusion results in 0 false alarms, but at a cost of low P_dP_c=0.744.

2) LLRT-based Fusion Algorithm Results

The orthogonal LLRT fusion algorithm was developed by extending the Lockheed Martin feature orthogonalization / LLRT classification algorithm, originally developed by Manuel Fernandez [19], to perform fusion. The confidences of the 4 CAD/CAC string outputs were combined to form a 4-dimensional vector, as shown in (9), which was utilized by the feature orthogonalization / LLRT fusion algorithm. If a particular call was not detected by a given CAD/CAC string,

TABLE 3. M-OUT-OF-N CAD/CAC FUSION SUMMARY

CAD/CAC String	*PdPc*	*FAPI*
Alg. 1 + 1	0.930	0.071
Alg. 2 + 1	0.907	0.159
Alg. 3 + 1	0.895	0.195
Alg. 4 + 1	0.860	0.204
1 out of 4	1	1.400
2 out of 4	0.942	0.283
mod. 2 out of 4	0.942	0.212
3 out of 4	0.895	0.062
mod. 3 out of 4	0.895	0.062
4 out of 4	0.744	0

the feature vector value at the corresponding location was originally arbitrarily set to zero [6].

The feature orthogonalization / LLRT fusion algorithm block diagram was shown in [11] (*Fig. 7*). In the training phase of the algorithm the learning vectors are processed through a feature orthogonalization and matrix transformation extraction procedure. This stage can be used to remove redundant information and reduce the dimensionality of the orthogonal feature vector set. Histograms are formed for each orthogonal feature and the LLRT values are computed and stored in a library.

In the testing stage of the procedure, each test vector is transformed via application of a transformation matrix, and the histogram libraries are used to look-up the log-likelihood-ratio values; these are then summed to obtain the overall composite LLRT value. The advantages of the fusion algorithm described include: it enables application of an optimal decision rule (i.e. the LLRT), entails very low complexity, and enhances visualization of the utility of each transformed feature.

A new investigation was presented in [7], i.e. if no detection, what to set the corresponding confidence value to. It was shown that for the case of no detection, setting the corresponding confidence value to C_{ij} = 0.125, 0.25 or 0.375 provides a small, but noticeable performance improvement, over the previously utilized case [6] of C_{ij} =0. This investigative work was repeated with the SW dataset and similar results were obtained.

The best fusion algorithm performance was obtained by utilizing the orthogonal LLRT fusion algorithm. The LLRT-based algorithm fusion results, for the case when the algorithm was *trained on all data*, are summarized in Fig. 6. The advantages that fusion provides over any individual CAD/CAC string are obvious (e.g. 8:1 false alarm reduction over the best performing single CAD/CAC string, while maintaining the same probability of correct target classification). Alternatively, fusion can drastically increase the correct target classification probability, as compared to the best single CAD/CAC string performance (i.e. fusion provides P_dP_c=0.988 at a FAPI = 0.257, whereas the Alg. 1 string results in P_dP_c = 0.93 at FAPI = 0.177). Thus, thanks to fusion one was able to correctly call 85 out of 86 targets, whereas the Alg. 1 string only correctly classified 81 of them, but with fusion we had the cost of a small increase in false alarms.

Fig. 7 summarizes the fusion results for the main approaches investigated: majority-voting and LLRT-based fusion. It is noted that LLRT-based fusion (when *training on all data*) provides the best results, providing an additional 11:1 false alarm reduction over “modified 2-out-of-4” fusion, while maintaining a constant mine classification probability of P_dP_c=0.942.

In the results just presented the fusion algorithm was trained on all the data and was tested on the same data. Some performance degradation should be expected if the algorithm is trained on a training set only and tested on all the data. In general, this is the preferred approach, since it results in a more robust design, and it will be the one employed when designing the algorithm parameters for future planned real-time demonstrations.

In previous work [9]-[10] the authors had investigated the LLRT-based fusion algorithm performance, for the case when the algorithm was trained on *training set data only* and *on test set data only*. In this case, the fusion algorithm, experienced a 2:1 increased false alarm performance degradation, as compared to the case where the algorithm was trained on all the data. Nevertheless, referring to Fig. 7, even if the LLRT-based fusion algorithm experienced a 2:1 increased false alarms performance degradation, it would still significantly outperform the “M-out-of-N” algorithms. Therefore, the LRRT-based algorithm is the recommended CAD/CAC string fusion approach.

This section has shown the performance gains provided by using LLRT-based fusion to combine the outputs of 4 distinct CAD/CAC processing strings. This raises the question whether one needs to use all 4 CAD/CAC strings and what performance will be obtained if one uses only 3 or even only 2 processing strings. The authors therefore utilized the LLRT-based procedure to fuse the CAD/CAC strings of algorithms 1 and 2 (the top 2 performing algorithms) and to fuse the CAD/CAC strings of algorithms 1, 2 and 3 (the top 3 performing algorithms). The results are shown in Fig. 8. It is noted that using LLRT-based fusion of 2 algorithms only, provides:

- A 1.7:1 false alarm reduction over the best performing string (algorithm 1), at P_dP_c=0.93.
- The capability to detect 84 out of 86 targets, at a low false alarm rate of FAPI=0.30.

Referring again to Fig. 8, it is noted that LLRT-based fusion of strings 1,2 and 3 provides:

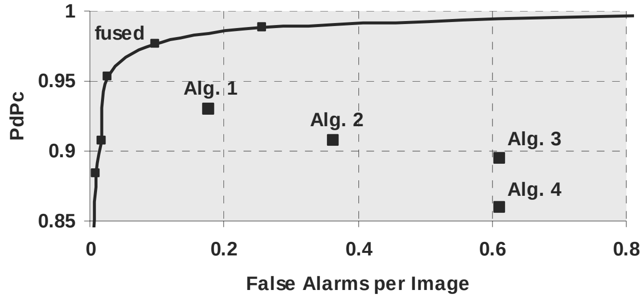

Fig. 6. LLRT-based fusion results (train on all data).

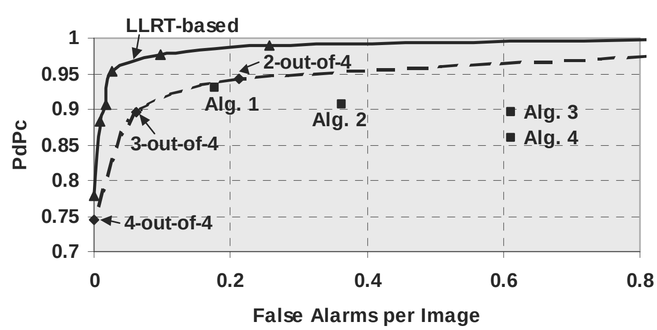

Fig. 7. Majority voting and LLRT-based fusion algorithm comparison.

- An 8:1 false alarm reduction over the best performing string (algorithm 1), at P_dP_c=0.93.
- An increased mine classification probability of P_dP_c=0.977, at a very low false alarm rate of FAPI=0.08.
- The capability to detect 85 out of 86 targets, at the cost of an increased false alarm rate of FAPI=0.64.
- An additional 4.8:1 false alarm reduction vs. the string that fuses 2 algorithms, at P_dP_c=0.93.

Finally, referring again to Fig. 8, it is noted that LLRT-based fusion of all 4 processing strings provides:

- An 8:1 false alarm reduction over the best performing string (algorithm 1), at P_dP_c=0.93.
- The capability to correctly call 85 out of 86 targets, at a cost of slightly increased false alarm rate vs. the best performing algorithm.
- The capability to correctly call all 86 targets, but at the cost of increased false alarm rate of FAPI=1.
- An additional 2.5:1 false alarm reduction vs. the string that fuses 3 algorithms, at P_dP_c=0.988.

Thus, each added processing string provides improved fusion performance, in terms of false alarm reduction and improved target classification capability, even when adding processing strings that on the surface appear to be much worst performers than the ones already being utilized. It should also be noted that performance of algorithms varies with different datasets. Thus, with a different dataset, algorithms 3 and 4 could be the top performers and 1 and 2 could be the worst ones. Therefore, only by utilizing as many distinct algorithms as possible, and their fusion, one can attain robust system performance in a variety of environments. Additionally, each algorithm developer is constantly striving to improve performance with each new sensor and datasets as they become available.

IV. CONCLUSIONS

A new, automated sea mine CAD / CAC processing string has been developed and successfully tested with real high-resolution sonar imagery data, collected in a shallow water environment. This robust processing string involves the fusion of the outputs of an assortment of mine classification algorithms. The overall CAD/CAC processing string includes pre-processing, adaptive clutter filtering (ACF), normalization, detection, feature extraction, feature orthogonalization, optimal subset feature selection, classification and fusion processing blocks.

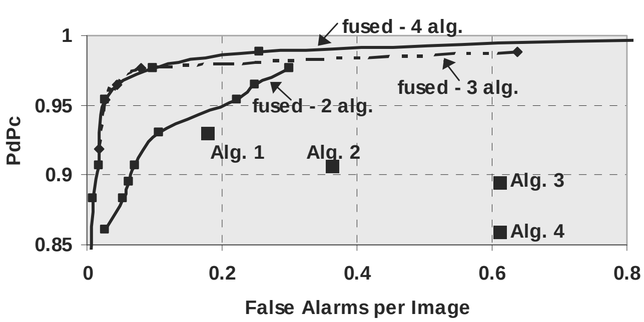

Fig. 8. LLRT-based fusion investigation: performance gains provided by fusing 2, 3 or 4 CAD/CAC strings.

Pre-processing includes image pre-normalization, clipping, data decimation and mean subtraction. The ACF is an adaptive linear FIR filter that is optimal in the Least Squares sense, and is applied to low-resolution data. A range dimension ACF is utilized, that is matched both to average highlight and shadow information (normalized mine target shape, obtained by prior data analysis from a training set), while simultaneously suppressing background clutter. Application of post-ACF normalization, removes any remaining data non-stationarities, whereas the following detection consists of thresholding, clustering of exceedances into objects (based on the expected mine size), limiting the number of detections and rejecting point-like objects.

Subsequently, features are extracted from high-resolution input data and an orthogonalization transformation is applied to the features, enabling an efficient application of the optimal log-likelihood-ratio-test (LLRT) classification rule. Two significant improvements were made to the CAD/CAC processing string by employing sub-image adaptive clutter filters (SACF) and utilizing a repeated application of the subset feature selection / classification blocks.

The utility of the Lockheed Martin's CAD/CAC processing string and the CAD/CAC processing string fusion was demonstrated with a new shallow water data set. The processing string detection and classification parameters were tuned and the string classification performance was optimized, by appropriately selecting a subset of the original feature set, at each classification stage in the multi-stage design classification process. The SACF-based improved CAD/CAC processing string resulted in increased target detectability, P_dP_c=0.93, vs. P_dP_c=0.91 that was previously obtained with the baseline single filter per image ACF-based CAD/CAC processing string. The cascade classifier based CAD/CAC processing string resulted in a 3.6:1 false alarm reduction, vs. the baseline single stage classification string that was previously utilized.

The classified objects of four distinct processing strings, developed by four different research teams, were fused using the classified objects' confidence values as features. The fusion approaches investigated included "M-out-of-N" and LLRT-based fusion. Best performance was obtained by utilizing LLRT-based fusion, and *training* the algorithm *on all the data*. The LLRT-based fusion resulted in an 11:1 false alarm reduction improvement over the "2-out-of-4" rule. A "modified 2-out-of-4" rule was also developed which provided a 25% false alarm reduction over the baseline "2-out-of-4" fusion rule.

The overall CAD/CAC processing string LLRT-based fusion resulted in improved mine classification capability, providing up to an eight-fold false alarm rate reduction, compared to the best single CAD/CAC processing string results. Alternatively, the LLRT-based fusion of the CAD/CAC strings provided excellent mine classification performance (P_dP_c=0.988, with only FAPI=0.257). Even when training the LLRT algorithm on *a training set only*, it still significantly outperforms the "2-out-of-4" fusion. Therefore, the LLRT-based fusion algorithm is the recommended fusion approach.

A new investigation was presented illustrating the performance gains provided by utilizing LLRT-based fusion of 2, 3 or 4 processing strings. Each added string provides a performance gain, in terms of false alarm reduction and/or increased mine classification capability, even when adding strings that appear to be significantly worst performers. Thus it is recommended, to utilize as many distinct algorithms as possible and their fusion, aiming to attain robust overall CAD/CAC system performance in a variety of environments.

Future plans include evaluating the effectiveness of the overall SACF, detection, feature extraction and orthogonalization, LLRT classification and LLRT-based fusion string with new sensor data, and implementing and testing the overall CAD/CAC and fusion processing string in real-time on board the UUV.

This paper has presented single CAD/CAC and fused processing string results with new SW high-resolution data. Although it is very tempting to put undue emphasis on the single string that provides the best classification results, one must refrain from doing so for a variety of reasons. First of all, the results presented here are preliminary and all four research teams are striving to improve their CAD/CAC string performance. Second, if a given processing string provides the best results with a particular dataset, there is no guarantee that it will provide the best results with a different dataset. Thus, the emphasis must be placed on the performance gains provided by fusing drastically different strings, providing improvement both in terms of false alarm reduction and/or increased correct target classification capability.

It must also be noted that the results presented here were obtained with a benign dataset. When recently processing other datasets, including a newer extensive more difficult VSW dataset, the need to develop processing string improvements has become evident.

ACKNOWLEDGMENT

This work was sponsored by the Office of Naval Research (ONR 3210E, ONR 32MIW). The technical agent was NSWC Coastal Systems Station, Dahlgren Division (POC: Dr. Gerald J. Dobeck).

The authors of this paper would like to thank Dr. Gerald J. Dobeck (CSS), Dr. Marty Bello (Alphatech), Bill Zurawski and Charles Ciany (Raytheon) for providing them with the outputs of their CAD/CAC processing strings, without which this fusion work would not have been possible.

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